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Optimized fault detection in bearings of rotating machines via batch normalization-integrated bidirectional gated recurrent unit networks

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ABSTRACT

Motor is commonly used in industrial applications. Although motors are frequently found to have bearing problems, this causes a serious safety risk to industrial production. Traditionally, fault diagnostics methods often required only signal processing techniques and are ineffective. To overcome this problem, deep learning (DL) has been recently developed rapidly and achieved remarkable results in fault diagnosis. The intelligent fault diagnosis and classification of rolling bearing faults based on ensemble empirical mode decomposition (EEMD) and batch normalization (BN), principal component analysis (PCA) based stacked bidirectional-gated recurrent unit (Bi-GRU) neural network, is proposed in this paper. BN is introduced to improve the fast convergence of gated recurrent unit (GRU). EEMD is applied to eliminate the noise interference from the vibrational signal, and then important features are selected using the correlation coefficient value. Next, PCA is utilized for dimensionality reduction to retain only the essential. Finally, the BN based stacked Bi-GRU model is developed to classify faults based on extracted features. The proposed model correctly classifies the different types of faults in real operating conditions and also compared with existing techniques.

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1. INTRODUCTION

Machine fault diagnosis is essential for detecting and classifying failures in rotating equipment, which are especially prone to defects like bearing, gear, and stator faults [1], [2]. These faults often generate unique vibration patterns that can indicate the machine's health status. Condition-based monitoring (CBM) has become a preferred maintenance strategy due to its ability to detect problems early, minimize downtime, and reduce maintenance costs [3]. Researchers have increasingly turned to artificial intelligence (AI) and expert systems to enhance the reliability and accuracy of such monitoring techniques. However, signal noise remains a major obstacle, complicating fault detection efforts [4], [5].

Traditional techniques like fast Fourier transform (FFT), envelope analysis, and high-frequency resonance methods have been widely used [6]–[8], though their effectiveness is often limited in complex, non-linear environments [9]. Recent methods, including wavelet transforms and empirical mode decomposition (EMD), offer improvements but still face challenges related to basis function selection [10]. Ensemble empirical mode decomposition (EEMD) addresses these shortcomings by reducing mode aliasing, thereby enhancing diagnostic accuracy in noisy conditions [10], [11]. When combined with deep learning (DL) approaches such as recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU), which are well-suited for time-series analysis, the overall diagnostic performance improves significantly [12], [13]. GRU, in particular, offers computational advantages, and batch normalization (BN) helps speed up network training [14]. This innovation has significantly improved the performance of neural networks in various domains, including fault classification in rotating machinery. Thirukovalluru *et al.* [15] employed an autoencoder for fault prediction, achieving good accuracy. Chen and Li [16] applied statistical bearing signals to a sparse autoencoder, combining it with a deep belief network for fault classification. Neural networks have also proven effective in addressing complex sequential data, with LSTM networks being used to calculate the remaining useful life (RUL) of machines and identify fault probabilities [17], [18]. Yu *et al.* [19] further demonstrated that LSTM models could achieve fault diagnosis accuracy up to 99% by automatically extracting dynamic information from raw data. In addition, Chen *et al.* [20] applied convolutional neural networks (CNN) to extract fault features from raw data, followed by LSTM for fault identification. Huang *et al.* [21] utilized EMD for noise reduction and a convolutional recurrent neural network (CRNN) for classifying rolling bearing faults. The research in [22], [23] employed EEMD to extract energy entropy as input features, later using support vector machines (SVM) for fault classification. Hinchi and Tkiouat [24] developed a convolutional long short-term memory (CLSTM) neural network, using CNN for feature extraction and LSTM for predicting RUL. Peng *et al.* [25] proposed a fault diagnosis method based on a bidirectional-gated recurrent unit (Bi-GRU), which efficiently captures dynamic information from time-series vibration data. Similarly, Zhiwei [26] designed a one-dimensional convolutional (1DCNN)-GRU model to handle sequential data for fault diagnosis. Wang *et al.* [27] proposed a Bi-GRU model that eliminates the need for pre-processing and achieves superior results in fault classification.

In this work, a Bi-GRU neural networks is proposed to diagnose the faults. The model is proposed to classify different types of faults in rotating machinery under varying operational conditions. The aim of this work are as follows. First, the vibration signal is transformed into both the time and frequency domains, and EEMD is applied to obtain intrinsic mode functions (IMFs). Correlation coefficients are used to select important features based on their significance and principal component analysis (PCA) is used for features extraction. Second, a Bi-GRU network is utilized to learn these features, with BN employed to enhance the model's training speed and accuracy. Finally, the developed model is compared with other machine learning techniques, demonstrating its superior performance in fault classification. This research proposed a highly efficient fault diagnosis framework that addresses key limitations in conventional methods. By integrating EEMD, correlation coefficient-based feature selection, and Bi-GRU with BN, the developed model achieves improved fault classification accuracy and faster training times, making it a valuable tool for industrial applications. The innovative aspects of this work lie in its ability to non-stationary signals, providing a robust solution for real-world fault diagnosis.

2. PROPOSED METHODOLOGY

In this research, an optimized fault detection method for rolling bearings in rotating machines was developed using a BN-integrated stacked Bi-GRU neural network model. Initially, vibration signals were obtained from bearings under normal and faulty conditions at various operating speeds. These signals were first converted into time and frequency domains for analysis. To remove noise and decompose the signals, EEMD was applied, resulting in multiple IMFs. To ensure that only the most relevant and noise-free features were selected for classification, the correlation coefficients between the IMFs and the raw vibration signals were calculated. This allowed for the selection of the best IMFs for fault diagnosis. Next, PCA is applied for dimensionality reduction, preserving only the most significant features from the IMF data corresponding to five distinct fault conditions. The extracted features were then input into a stacked Bi-GRU model, which was enhanced by the incorporation of BN to accelerate convergence and improve the learning process. The architecture was trained using several hyperparameters, including the Adam optimizer, mean squared error as the loss function, a batch size of 50, a dropout rate of 0.2, 50 epochs, and a learning rate of 0.01. The model effectively handled sequential data and exploited bidirectional dependencies for more accurate fault classification. To evaluate its performance, the model was trained, tested, and validated with a bearing dataset. Results were assessed using a confusion matrix, revealing high accuracy in classifying various bearing conditions. Additionally, receiver operating characteristic (ROC) curves were used to evaluate the model's performance across different thresholds, confirming its effectiveness in fault detection.

The vibration signals from the fan-end (FE) and drive-end (DE) bearings, collected from a data repository at http://engineering.case.edu/bearingdatacenter, represent normal and faulty conditions at varying speeds of 1730, 1750, 1772, and 1797 rpm as shown in Table 1. These signals are observed to contain high levels of stationarity and noise, posing significant challenges in fault identification using conventional feature extraction techniques. As shown in the methodology at Figure 1, EEMD was employed for both noise removal and the extraction of IMFs without mode mixing. The IMFs with low non-stationarity and high correlation with the raw signals were selected as features. These filtered features were then fed sequentially into a stacked Bi-GRU model for classifying bearing conditions. The raw vibration data from FE and DE bearings under different conditions and speeds were analyzed in both time and frequency domains. Frequency spectrum analysis is a common technique to identify bearing defect frequency components by applying the FFT. In this work, the original vibration signals were converted into the frequency-amplitude domain, and EEMD was applied to decompose the signals into several IMFs (IMF 1 to 14) and residuals. Each IMF showed different frequency components, with high-frequency content shifting to low-frequency content during decomposition. Noise removal improved at higher decomposition levels, and by IMF 14, frequency components were well isolated.

Table 1. Rolling bearing state

Bearing state (Approx motor speed (rpm)=1730, 1750, 1772, 1797		
No.	Fault diameter (inches)	Fault location
1	-	Normal condition (NC) (Class 0)
2	0.007	Inner race fault (IRF007) (Class 1)
3	0.021	Inner race fault (IRF021) (Class 2)
4	0.007	Outer race fault (ORF007) (Class 3)
5	0.007	Outer race fault @ (6:00)a (ORF007@6) (Class 4)
6	0.014	Outer race fault @ (12:00)a (ORF014@12) (Class 5)

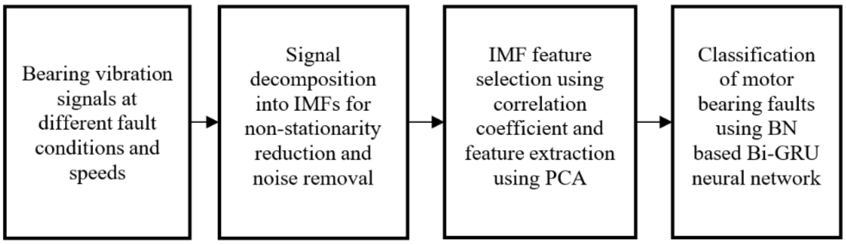

Figure 1. Combinational framework for classification of bearing faults

2.1. Feature selection

Any classification model performs best when trained on significant features while avoiding noise. Though EEMD effectively decomposes signals, it increases input data. To address this, correlation coefficients between the decomposed IMFs and raw signals are calculated to select the best denoised and highly correlated IMFs. The application of EEMD and feature selection using correlation coefficient finally has given a set of 8 IMF features each of sample length 15,000 for six bearing conditions [8×6×15000].

2.2. Feature extraction and dimensionality reduction

PCA was performed on the initial feature space of [8×6×15000] in order to reduce the dimension and also to further remove the data redundancy. All the selected IMFs have been reduced along two principal components since they captured most of the variance in the data and the resulted data size is of [2×6×15000] for each of the bearing condition. The reduced feature vectors for all six conditions are fed as input for training the neural network.

2.3. Fault diagnosis based on batch normalization stacked bidirectional-gated recurrent unit

The fault diagnosis algorithm is divided into two sections. The first is to capture the dynamic information from raw data and the second is to develop a DL classifier model for classifying the various types of bearing faults under different conditions. The framework of the proposed algorithm is shown in Figure 2. The following steps are given:

i) Collect the sensors data. Then, the data is preprocessed and scaled (ranges from 0 to 1).
ii) Application of EEMD on vibrational signal which analyses in time-frequency domain.
iii) Selection of features is done by correlation coefficient.

iv) Reduction of high dimension feature space into low dimension using PCA.
v) Split the prepared dataset into train, validation and test data
vi) BN is used to speed up training, stabilize the learning process, and potentially improve the generalization of the neural network
vii) Train and develop the BN based stacked Bi-GRU.
viii) The performance of the proposed algorithm is confirmed by accuracy, model loss, confusion matrix, and ROC area under the curve (AUC) curve.

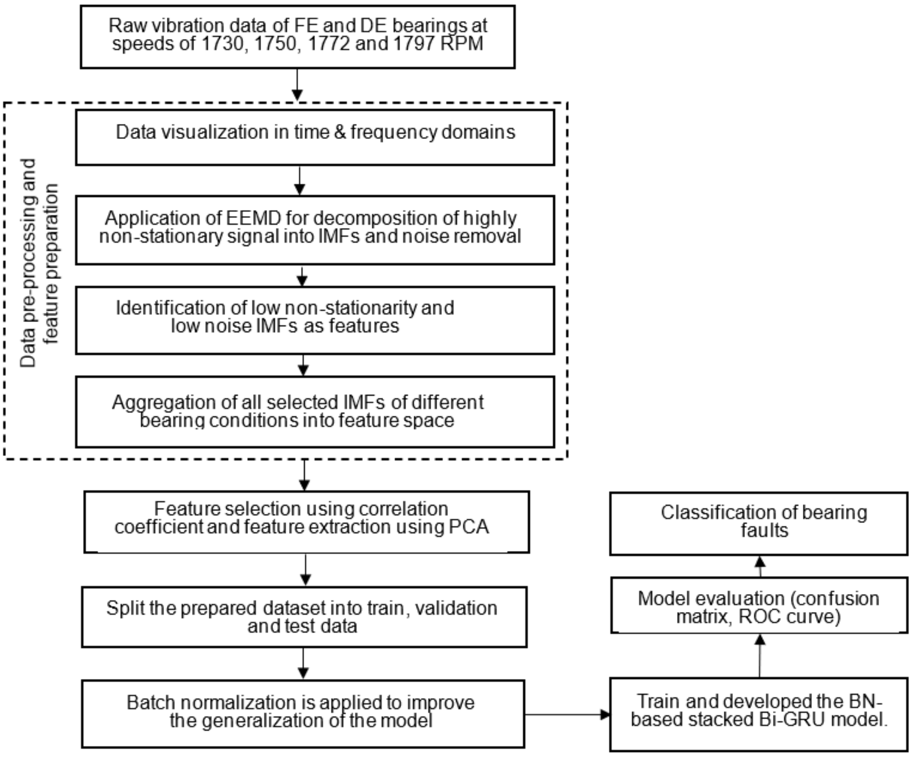

Figure 2. Framework of proposed algorithm

2.4. Stacked bidirectional-gated recurrent unit model for classification of bearing conditions

The stacked Bi-GRU model [27], composed of two GRU layers in sequence, leverages information from both time directions to classify bearing conditions. Increasing the number of Bi-GRU layers theoretically enhances feature extraction and improves fault classification accuracy. However, adding multiple GRU layers also increases training time and risks overfitting. To maintain effective processing, the argument 'return_sequences' is set to 'True', ensuring the output of each GRU layer is reshaped into a 3D array and passed to the next layer. In this work, four different types of multi-layered, BN based stacked Bi-GRU models were trained to classify the conditions of roller bearings, with their performances compared to one another. The bearing dataset was splitted into training, testing, and validation sets. During each epoch, the model was trained using the training dataset and automatically validated with 2% of the trained data to prevent overfitting and improve parameter selection. The hyperparameters used for training are as follows: Adam optimizer, mean squared error loss function, batch size of 50, dropout rate of 0.2, 50 epochs, and a learning rate of 0.01. The entire framework is developed and trained using the Python programming language, with Keras and TensorFlow 1.0 libraries for implementation.

3. RESULTS AND DISCUSSION

In recent years, researchers have looked at different methods for diagnosing faults in rotating machines. They often use techniques like wavelet transform and EMD, including a variation called EEMD. However, these methods struggle with noise and mode mixing, which can make them less effective in real-world situations. Traditional machine learning methods also rely on manually selecting features, which can lead to poor performance if the features are not chosen correctly. This study introduces a new method that uses EEMD to remove noise and a stacked Bi-GRU neural network with BN for better feature selection and classification. We found that EEMD greatly reduces noise in vibration signals, improving the quality of data for classification. By using correlation coefficients, we selected the most important features from these signals. The BN-based Bi-GRU model achieved high accuracy in identifying different types of bearing faults. It also trained faster and performed better than traditional methods like CNN and LSTM. However, there are some limitations, such as the dataset being collected under controlled conditions, which may not represent real-world scenarios. Future research should focus on improving feature selection to address these issues.

Table 2 compares the testing accuracy of various DL models, showing that LSTM, Bi-LSTM, GRU, and Bi-GRU achieved moderate accuracy (82.92 to 86.80%), while the proposed BN-based stacked Bi-GRU network outperformed all others with a perfect 100% accuracy. The key findings demonstrate that applying EEMD to preprocess vibration signals effectively reduces noise and enhances the quality of input data for classification. The proposed method resulted in a significantly higher proportion of important features being selected through the correlation coefficient from the decomposed signals, compared to traditional approaches. The BN-based Bi-GRU model also exhibited faster convergence and superior fault classification accuracy compared to existing methods such as CNN, LSTM, and SVM, making it particularly suitable for real-time industrial applications.

Table 2. Accuracy of classification models

Models	Testing accuracy (%)
LSTM	84.90
Bi-LSTM	86.80
GRU	82.92
Bi-GRU network	83
BN-PCA based stacked Bi-GRU network (proposed)	100

The classification accuracy of the BN-based stacked Bi-GRU model was compared with other machine learning and DL models from the literature [28]–[31]. Table 3 shows that the proposed model outperformed existing methods, achieving superior results compared to the 1D-CNN-LSTM (97.69%), SVM (56.2%), random forest (55.5%), RNN (60.1%), XGBoost (94%), neural network (55.5%), Attention LSTM (84.73%), and LSTM (91.79) models. Additionally, the ROC curve, a key evaluation metric, was used to assess the model’s fault classification performance. Figure 3 indicates a strong true positive rate, with AUC values for each fault class ranging from 0.82 to 0.93, confirming the model's reliability for bearing condition classification using raw vibration data.

This study examined a comprehensive fault diagnosis model using the proposed stacked Bi-GRU architecture with EEMD for feature selection. However, further research may be needed to validate its effectiveness, particularly regarding varying real-world industrial conditions and the presence of additional noise sources. While the EEMD and correlation coefficient methods were beneficial for selecting relevant features, the increased number of input signals may lead to higher computational demands, which future research should address by optimizing feature selection further. Our study demonstrates that the BN-PCA based stacked Bi-GRU model is more resilient than traditional fault detection methods for bearing diagnosis in rotating machines. Future studies may investigate hybrid models that combine DL with expert knowledge-based systems and explore feasible methods for producing more computationally efficient algorithms that maintain high classification accuracy while minimizing training time, particularly in real-time applications where data is continuously streamed. Figure 4 shows the confusion matrix of the proposed model, which correctly classifies the different fault conditions of roller bearings. The testing results, displayed in Figure 5, shows the enhanced performance of the stacked Bi-GRU model in classifying bearing conditions using process data.

Table 3. Comparison of classification accuracy

Methods	Testing accuracy (%)
RNN [29]	60.1
SVM [30]	56.2
XGBoost [31]	94
Random forest [29]	55.5
Neural network [29]	85
Attention LSTM [28]	84.73
1D-CNN-LSTM [28]	97.69
LSTM [30]	91.79
BN-PCA based stacked Bi-GRU (proposed)	100

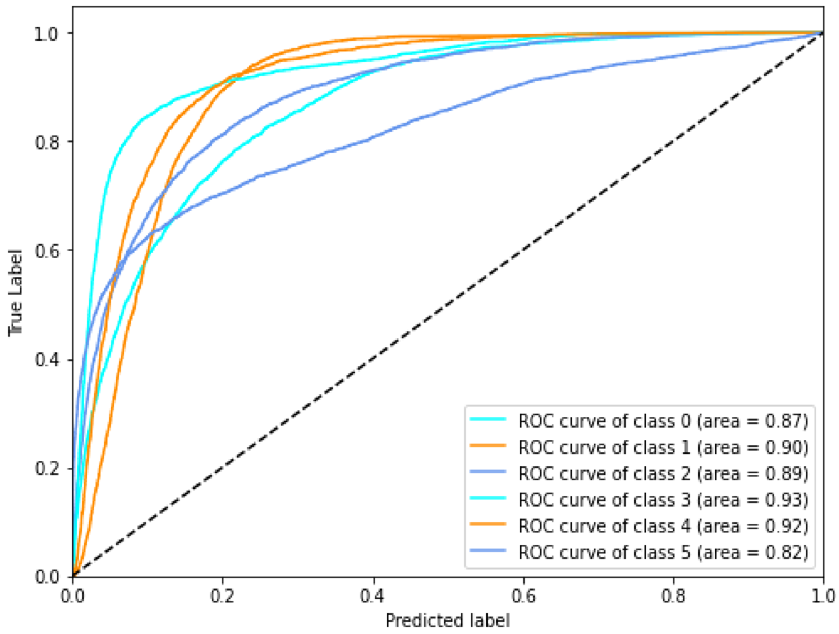

Figure 3. ROC curves of proposed model

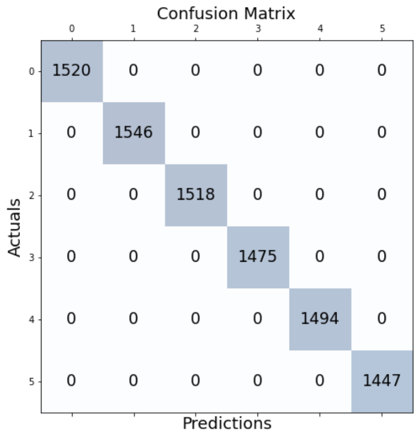

Figure 4. Confusion matrix of proposed model

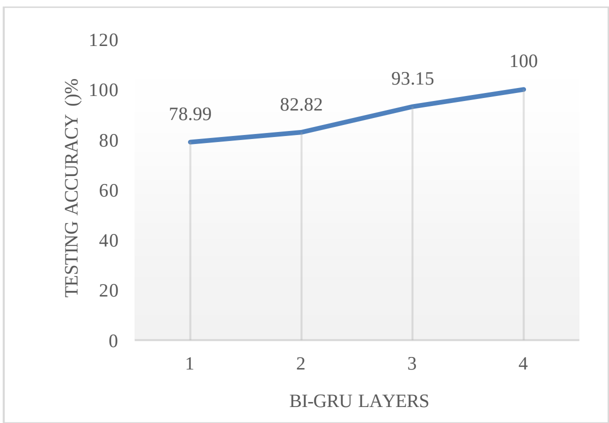

Figure 5. Testing accuracy of proposed model

4. CONCLUSION

Rolling bearing failures are common faults in rotating machines. In this paper, a BN-PCA-based stacked Bi-GRU model is developed. To handle non-stationary signals, EEMD is employed as a powerful tool to decompose vibrational signals into multiple IMFs. The correlation coefficient technique is then applied to select features from these IMFs. BN is used to accelerate model training and ensure fast convergence, and PCA is used for feature extraction. The proposed model accurately classifies different bearing fault conditions under various motor running speeds and has also been compared with existing methods. Recent observations indicate that the application of EEMD significantly reduces noise and enhances feature selection in the fault diagnosis of bearings. Our findings provide conclusive evidence that this approach is associated with faster convergence and superior classification accuracy, not only compared to existing techniques but also in the context of real-time monitoring and fault diagnosis in industrial environments. This work describes the importance of integrating advanced signal processing and DL methods for effective fault detection. Future work can extend this approach for implementation in real-time fault diagnosis.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Sujit Kumar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Manish Kumar	✓								✓		✓			
Chetan Barde	✓				✓					✓		✓		
Prakash Ranjan	✓				✓					✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Publicly available dataset has been referred in the manuscript.

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